北京航空航天大学四年级博士生和五年级直博生
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承担科研任务情况	项目名称	课题来源	课题负责人	本人承担的具体工作
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已取得研究成果（论文、专利、获奖等）	论文题目	本人排名	发表年月	期刊（会议）名称	被检索类型
	Quantitative EEG in Mild Cognitive Impairment and Alzheimer’s Disease by AR-Spectral and Multi-scale Entropy Analysis	1	2018.6	The World Congress on Medical Physics and Biomedical Engineering 2018	2EI/3ISTP
	A Hybrid BCI-based Environmental Control System Using SSVEP and EMG Signals	1	2018.6	The World Congress on Medical Physics and Biomedical Engineering 2018	2EI/3ISTP
	Quantitative EEG in Mild Cognitive Impairment by AR Spectral and Multi-scale Entropy Analysis（one-page）	1	2017.7	The 39th Annual International Conference of the IEEE Engineering in Medicine and Biology Society	2EI/3ISTP
	A Hybrid BCI based on SSVEP and EMG of temporalis for Home control	2	2018.4	The 12th International Convention on Rehabilitation Engineering and Assistive Technology	2EI/3ISTP

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Quantitative EEG in Mild Cognitive Impairment and Alzheimer's Disease by AR-Spectral and Multi-scale Entropy Analysis

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Abstract.
To assist effective and precise diagnosis for mild cognitive impairment(MCI) and Alzheimer's disease(AD),Electroencephalograph(EEG) has been widely used in clinical research of patients with AD at MCI state. To study the linear and non-linear abnormality of EEG in AD and MCI patients, multiple characteristics was applied to distinguish AD and MCI patients from the normal controls(NC). EEG signals was recorded from 28 subjects, including 10 AD patients, 8 MCI subjects and 10 healthy elderly people. EEG signals in all channels was computed by auto-regressive model and multi scale entropy(MSE) to obtain relative power spectral density (PSD) value of each frequency band and entropy value in different time scales. Area under Receiver operating characteristic curve (AUC) was used to compare the classification ability of the two method. The ratio Alpha/theta of MCI group in left frontal area can distinguish MCI from NC subjects. Also the long scale entropy value in left frontal-central area manifests a better accuracy in distinguish AD and MCI from NC group. In addition, the combined feature from alpha/theta and long scale entropy in the left frontal central area can discriminate AD from NC group with higher AUC reaching 0.89. This indicated that combined PSD and MSE can be taken as a potential measure to detect AD in early state.

Keywords: Nonlinear, Multi-scale Entropy, Alzheimer's Disease, Mild cognitive impairment.

1 Introduction

Alzheimer's disease is a degenerative diseases of the central nervous increasingly affects the elderly people, causing loss in cognition, memory, even language function [1].About 10-15% of MCI elderly people each year developed into AD, effective diagnosis and treatment for MCI is very important [2]. The clinical detection of MCI and AD is mainly based on subjective neuropsychological test [3]. The imaging method was used to study the brain structure changes of MCI and AD, but its specificity is not high in the early stage of AD [4]. Also the detection based on biomarkers is invasive

[5]. EEG can reflect the physiological activities of the brain, and because of its low-cost, non-invasive and high time resolution, it has been widely used in clinical research of patients with AD at the MCI stage [6].
Quantitative EEG recordings in rest state provide an ideal methodology of the rapid detection in MCI and AD [7]. Babiloni et al [8] presented the hippocampus volume is related to the loss of alpha rhythms in AD. Moretti et al [9] found the alpha relative power of MCI in the frontal area was decreased, and power in theta band was increased. Compared with traditional spectrum estimation, the parameter estimation based on AR model performs better, it has been used to calculate PSD of EEG in MCI studies [10].
Although linear analysis is important to quantify the abnormal EEG rhythm of patients with MCI or AD, considering the non-stationarity and randomicity of EEG signal, complexity measures such as entropy were widely used to analysis EEG in AD patients. Abasolo et al [11] showed the entropy of AD patients in the parietal area is lower than health elderly. Hogan et al [12] found that the entropy of MCI subjects was reduced. MSE analysis base on entropy can measure the probability of producing new information for sequences under different scales size, it has been used in cognitive neuroscience. Mizuno et al [13] found large scale entropy of AD patients in whole brain areas was higher than healthy elderly. Previous studies suggested the complexity changing of EEG signals related to cognitive impairment may be inconsistent in different time scales.
In this work to further quantify both linear and nonlinear comprehensive abnormality of EEG in MCI and AD patients, the PSD and MSE method was adopted to analysis the MCI, AD and normal elderly. Then we compared the accuracy of PSD value, MSE value and combined index in distinguishing AD and MCI from healthy elderly.

2 Subject and Experiment

2.1 Participants

Ten hospitalized AD patients from the department of neurology, JiangBin Hospital in NanNing, GuangXi province (China), and 18 volunteers over 60 years old were recruited. All subjects were right-handness, after clinical evaluation and neurological examinations, eight subjects whose MMSE score were ranged from 24 to 27 composed to be MCI group, other subjects composed to be NC group. Table 1. gives the information of subjects. '*' means difference of MMSE in three groups was significant. The difference in age, gender and education level are not significant.

Table 1. Information of Subjects

Heading level	NC(N=10)	MCI (N=8)	AD(N=10)	ANOVA P
Sex(female/male)	6/4	4/4	4/6	0.38
Age (years)	74.4±9.6	79.1±8.7	80.6±6.7	0.25
Education(years)	8.5±2.1	8.5±1.4	8.0±0.1	0.69
MMSE	28.9±1.2	24.6±0.7	16.9±1.5	0.00 *

2.2 EEG recording

The data collected by the NicoletOne EEG acquisition instrument with 16 channels, sampling rate is 250Hz. During the experiment the electrode impedance was kept under in 5KΩ, acquisition channel concludes Fp1, Fp2, F3, F4, C3, C4, P3, P4, O1, O2, F7, F8, T3, T4, T5, T6. Five minutes EEG signal was collected in rest state with eyes closed. Five segment of 5 seconds which has no obvious interference in all channels was selected for subsequent processing. EEG signal was preprocessed by 0.05–40Hz band pass filter, all data was processed in MATLAB (R2012a).

3 Method

3.1 Power spectrum density (PSD)

PSD analysis for each segment is estimated using AR Burg method, which is one of the most frequently used parametric method. AR model is based on modeling the data sequence as the output of a causal and discrete filter whose input is white noise. Thus the AR model of order p is expressed by the difference equation. AR parameters was estimated by the Burg algorithm, and the optimal order of AR model was estimated by the final prediction error criterion (FPE). The PSD in each frequency band was normalized to obtain the relative PSD, where the sub-band was selected as delta band in 0.5-4Hz, theta band in 4-8Hz, alpha band in 8-13Hz and beta band in 13-30Hz. And alpha/theta which shows the ratio of PSD in alpha band versus theta band was computed.

3.2 Multi-scale entropy (MSE)

MSE is a method which measure the complexity of a finite length time series to quantify the probability of generating new information on different time scales. MSE method based on sample entropy of different scales was calculated as the following steps[13]: Firstly, for EEG time series X, construct a coarse-grained time series Y according to a scale factor, the length of reconstruction time series is M, in this work set m=2 to get the new time series Y_m. Secondly, quantify the sample entropy of each coarse-grained time series, the distance between each Y_m was computed. Set a threshold, r=0.25, the number of the distance less than r was calculated as B, then obtain the average ratio of this number to the total number of vectors. Lastly, for the next number of dimensions m+1, repeat the above steps to obtain the sample entropy of each scale from 1 to 20.

3.3 Statistical analysis

Comparison between groups (NC and MCI, MCI and AD, NC and AD) was made using the independent samples T-test. ROC curves was used to estimate the discriminating ability of PSD and MSE. Area under curve (AUC) of ROC near the upper left corner indicate diagnostic capabilities. Statistical procedures was performed using SPSS 19.0.

4 Results

4.1 MSE in different scales

The sample entropy value on 1 to 20 scales in each channel of AD, MCI and NC group was shown in "Fig. 1". For each scale we compared the difference between AD and NC group. The red box indicated that within this range of scales, differences was statistically significant between AD and NC group. The long scale entropy of AD group was greater than MCI group, and the value of MCI group was greater than NC group, especially for scales more than 12, there was significant differences in each channel of the left side brain areas.

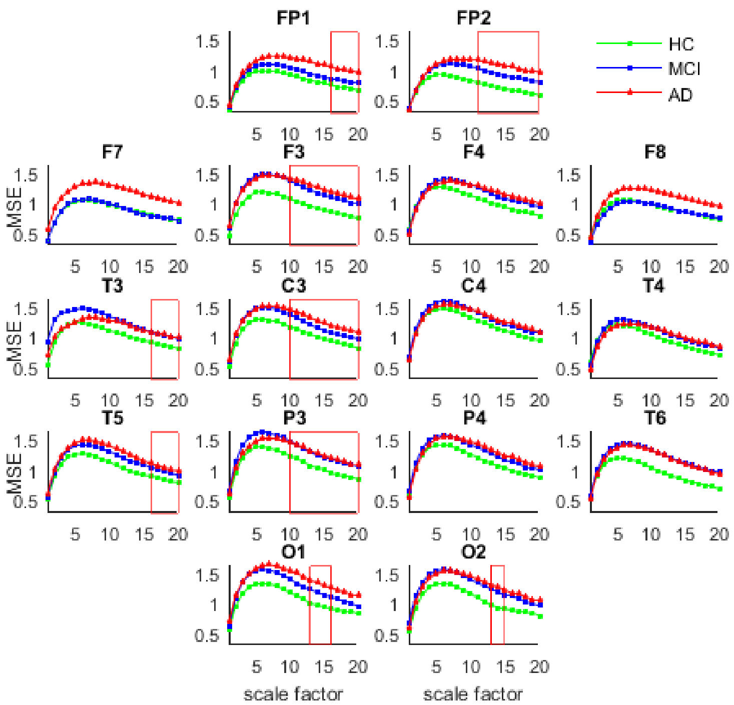

Fig. 1. MSE in different scales of different channel

The average entropy from 13 to 20 were computed as the long scale entropy value. The "Fig. 2" shows the long scale entropy in left frontal, left occipital, left parietal occipital, left temporal, right frontal, right occipital, right occipital area and right temporal areas, differences between AD and NC group were analyzed by t test. The long scale entropy value of AD group was greater than MCI group, and the value of MCI was greater than NC group. Especially the difference between AD and NC group in the left frontal, left frontal-central and left parietal-occipital areas was significant.

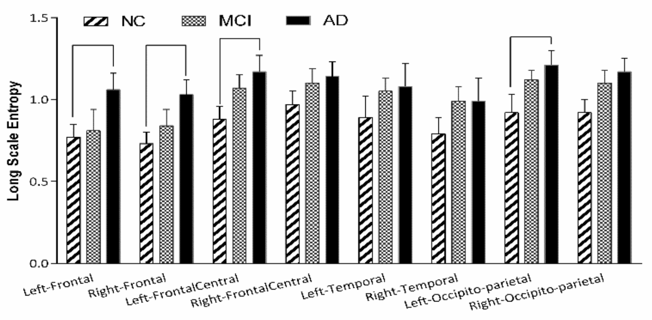

Fig. 2. Alpha/Theta in different areas

4.2 PSD in different band

The average PSD value of different frequency band in each channel of the three group was shown Table 2, '*' means difference between AD and NC group was significant, and '+' means difference between AD and MCI group was significant.

Table 2. PSD index of different frequency band

	β	α	θ	δ	(β+α)/(θ+δ)	α/θ
NC	0.18±0.03	0.41±0.05	0.24±0.02	0.16±0.04	0.72±0.34	2.91±0.33
MCI	0.15±0.02*	0.40±0.06	0.28±0.02*	0.16±0.05	0.60±0.33*	2.13±0.31*
AD	0.12±0.01^{*+}	0.33±0.05^{*+}	0.37±0.02^{*+}	0.19±0.06^{*+}	0.28±0.16^{*+}	0.95±0.12^{*+}

For Alpha/Theta, difference between groups on left and right side of four brain areas were also analyzed by t test. As shown in "Fig.3", the line means $p<0.05$, the difference was significant. There was significant difference of the alpha/theta value in left frontal, left temporal, right temporal and right parietal occipital areas. There was significant difference of the alpha/theta value in left frontal area of MCI and NC group. And there was significant difference of the alpha/theta value in right parietal occipital area of MCI and AD group.

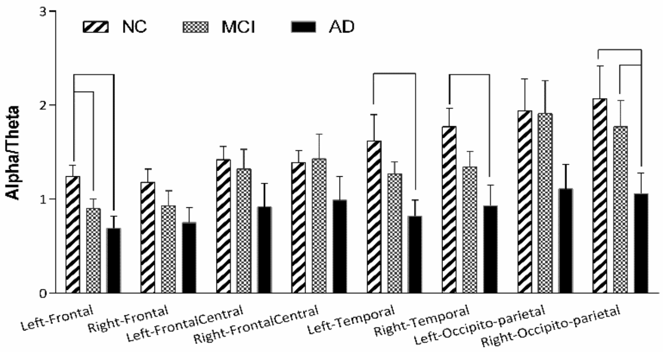

Fig. 3. Long-scale entropy in different areas

4.3 ROC analysis

AUC was used to assess the ability of index in discriminating AD and MCI from NC group, the AUC of alpha/theta and long scale entropy in eight areas was computed, as Table 3 shows, * means AUC is more than 0.7. The results indicated that the two indexes in left frontal-central and occipito-parietal areas has certain accuracy in discriminating AD from NC group. AUC of linear and nonlinear index in the Left Frontal-Central area was all more than 0.7, with 0.75 and 0.81. We further combined those two value in left frontal-central area to distinguish AD from NC group, the AUC of combined index reached 0.89, which is higher than AUC from any single feature.

Table 3. AUC of Alpha/Theta and long scale entropy

	AUC of Alpha/Theta		AUC of Long Scale Entropy	
Brain areas	AD and NC	MCI and NC	AD and NC	MCI and NC
L-Frontal	0.61	0.76*	0.77*	0.55
R-Frontal	0.68	0.56	0.80	0.54
L-FrontalCentral	0.75*	0.48	0.81*	0.73*
R-FrontalCentral	0.59	0.58	0.68	0.61
L-Temporal	0.56	0.69	0.65	0.58
R-Temporal	0.65	0.58	0.63	0.65
LOccipitoparietal	0.86*	0.55	0.74*	0.69
ROccipitoparietal	0.79*	0.74*	0.67	0.69

5 Discussion

In this study, linear and non-linear method, PSD and MSE analysis was employed to distinguish MCI and AD patients from normal elderly. Cognitive impairment is related to the spontaneous EEG activity rhythm, the abnormality of all the PSD index in MCI and AD patient was consistent with the prior studies. The significant declined power of alpha band in AD patients was indicated, and these values of MCI subjects also has a downward trend compared with normal elderly. The alpha/theta ratio in left frontal and right occipito-parietal areas can be a typical feature of cognitive decline, which discriminated MCI from normal elderly significantly.

For MSE analysis, we determined the appropriate range of scale to obtain long scale entropy value, the complexity abnormality of MCI patients was consistent with prior studies. The long scale entropy in left frontal-central and ccipito-parietal areas provided better classification performance between AD patient and normal elderly. And in left frontal-central area it also provided good classification performance between the MCI and NC. This manifests EEG abnormality in dominant side brain areas of AD patients is more notable. The complexity of EEG from MSE analysis can provide more information which may benefit our understanding of cognitive impairment.

Since the brain is a complex system showing both linear and nonlinear features, combining PSD and MSE which can reflect the rhythmicity as well as complexity, to obtain effective multiple quantitative EEG index in rest state, can be taken as a potential measure in early screen of AD.

Acknowledgments

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Conflict of Interest

The authors declare that they have no conflict of interest.

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A Hybrid BCI-based Environmental Control System Using SSVEP and EMG Signals

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Abstract.
The paper developed a hybrid Brain–computer interface (hBCI) home environmental control system for paralytics' active and assisted living, by integrating single channel Electromyography (EMG) of occlusal movement and steady state visual evoked potentials (SSVEP). The system was designed as three-level interface, besides the idle state interface, for work state there are one main interface and five sub-interfaces. The main interface included five visual stimulus corresponding to different devices such as nursing bed, wheelchair, telephone, television and lamps, the sub-interfaces present control function of those devices. Gazing at stimuli at different frequencies corresponding to a certain function can select a device or device action. Several particular occlusal patterns respectively are used to confirm the selected function, return from sub-interface to main interface and switch on/off the system. Ten healthy subjects without any training completed the virtual system verification experiment, the averaged target selection accuracy based on SSVEP achieved 96.3%. Moreover with a simple clench action for target confirmation, the false positive rate was minimized to zero, which improved the control accuracy. This indicated that Combining SSVEP and EMG can effectively enhance the security and interactivity of the environmental control system.

Keywords: Hybrid Brain Computer Interface, Environmental Control, Electromyography (EMG), Steady State Visual Evoked Potential (SSVEP), paralytics.

1 Introduction

Brain–computer interfaces is an alternative channel of neuromuscular pathway, which allows users to directly control a device by brain activity [1].The interest in BCI research is increasing as the rapid development of brain cognition and neuroscience, computer science and biomedical engineering. Particularly in rehabilitation engineering, BCI technology is potentially useful for people who are severe paralyzed after amputation, stroke or spinal cord injuries (SCIs), by reconstructing their communication with daily living environment [2].

Multiple Electroencephalography (EEG) paradigms have been used in BCIs, such as Motor Imagery (MI), P300 and Steady State Visual Evoked Potentials (SSVEP) [3]. Among those, BCI based on SSVEP received much attention as it can achieve higher information transmission rate (ITR) without training, and has been used for the control of nursing bed and wheelchair using SSVEP-BCI [4-6]. Those BCIs based on single EEG paradigm were used to control a single device, however communication with a variety of devices in home environment system is complicated. Moreover, single modal BCIs are usually synchronous and cannot distinguish idle state with work state automatically which is likely to cause wrong operation.

Considering those problems, researchers have proposed hBCI, combining two or more EEG paradigms to control complex devices. Pfortscheller et al. added an event related desynchronization (ERD) potential to SSVEP-BCI to realize the switch of the system [7]; Allison et al. used mu rhythm and SSVEP to achieve asynchronous control [8]; Li et al. combined SSVEP and P300 to reduce the false positive rate during idle state [9]. Other researchers developed hBCIs using different physiological signals from electrocardiogram (ECG), electrooculogram (EOG) or electromyogram (EMG), Lin K et al detected the EMG of hand movement to choose the location region of target in a SSVEP- BCI speller [10-12]. Nevertheless, for severe paralysis or amputees, only muscles above neck remain function, especially EMG of their occlusal movement is obviously suitable as a control signal [13].

In this paper, EMG signals from occlusal movement were integrated into SSVEP-BCI to build the hBCI home environmental control system. To validate the reliability of the system function, a virtual environmental control experiment was designed, the performance of target selection and confirmation, return and switch were evaluated.

2 Structure and method

2.1 System Modules

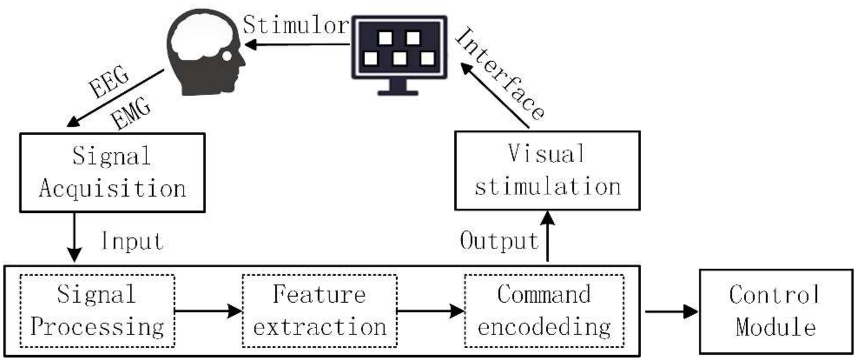

Fig. 1. System Modules

As shown in Fig 1, the hBCI home environmental control system includes visual stimulation, signals processing and results feedback modules. Visual stimulation was presented at the LCD monitor. The stimulation and signal processing program are written using MATLAB. The recognition results were encoded sending to the environmental control module.

2.2 Functional interface

As shown in the Fig 2, the system interface consists of three levels, which can be switched between each level. After switching from the idle state to work state, there were one main interface and five sub-interfaces. For wheelchair interface, the target corresponds to moving forward/backward, turning left/right and switching the posture to stand up or lay down. For nursing bed, the action includes rise/fall of the bed, flipping left/right and adjusting the angle of back and leg. For television interface, users can select the menu or turn back to the homepage. For telephone interface, there are three emergency numbers. For environment interface, there are two lamps and a curtain.

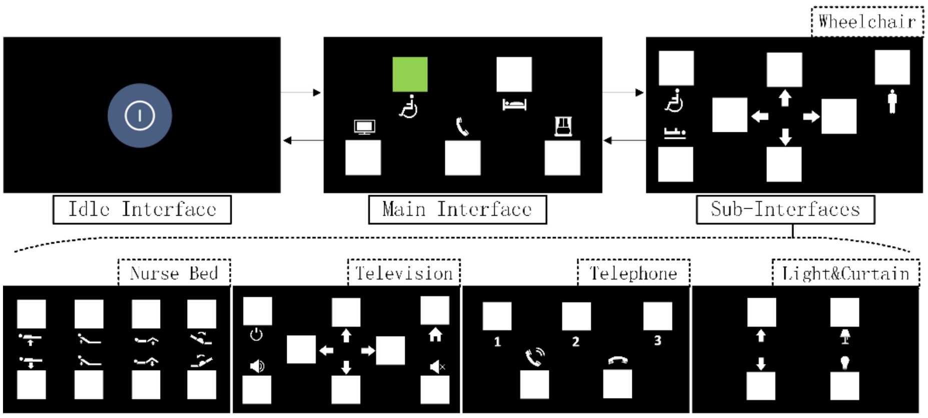

Fig. 2 Main interface and Sub-interfaces

2.3 Control Method

The system combined the recognition of three EMG patterns and SSVEP to design the control mode. The control flow is illustrated as Figure 3, during idle state, EMG pattern 3, a long-time clench was used as a switch to turn on the system. Two stages were needed from main interface to sub-interfaces, the of the target selection stage lasts three seconds, target confirmation stage duration was two second. In device-selection stage, devices on the main interface was chosen by gazing at the flicker. And the flicker corresponding to the certain function was labeled green when its SSVEP feature was recognized. In device-confirmation stage, EMG pattern 1, a one-time clenching was used to get into the sub-interface. Each sub-interface include different number of targets, functions of devices on the sub-interface also can be chosen through SSVEP recognition, then be confirmed by EMG pattern recognition. In all the sub-interfaces, EMG pattern 2, a two-time clenching was used to return to the main interface.

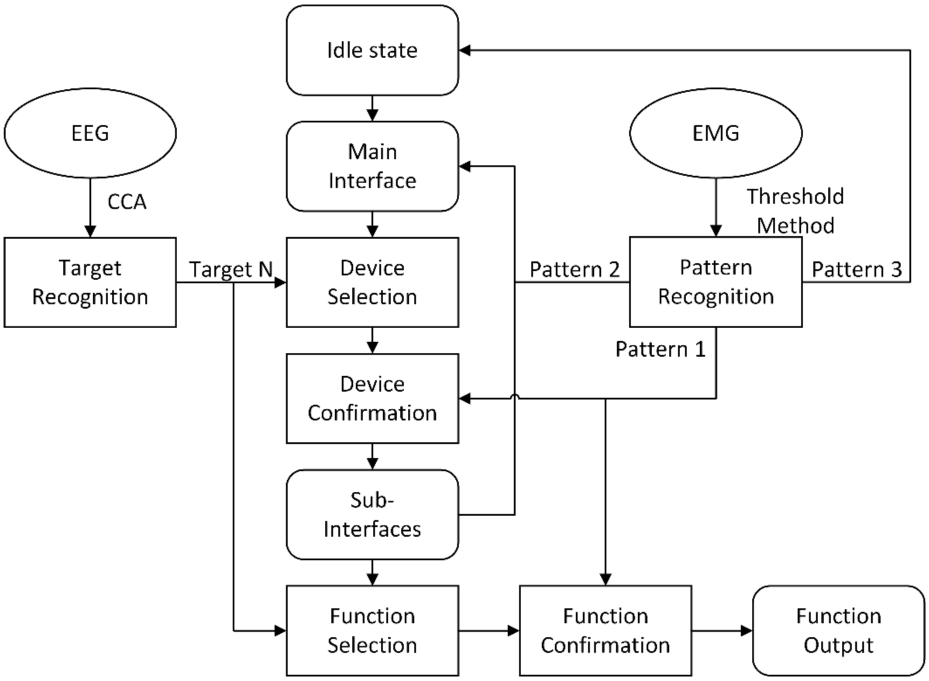

Fig. 3 Control Method

2.4 Signal Processing

The signal processing includes preprocessing and feature recognition. The classification method of SSVEP is Classical Correlation Analysis (CCA). EEG signals from occipital region channel of the brain (PO4, PO3, O1, O2) were selected to calculate the characteristics. The reference signals in CCA were composed of sinusoids and cosinusoids pairs at the same frequency of the stimulus and its second harmonics. Different frequencies of SSVEPs correspond to flicker in different position.

The pattern detection of EMG signals are based on the feature threshold method. Integrated EMG (iEMG) calculated in a window of a certain length was selected as the feature, and the appropriate threshold were used to detect the number of exceed points upon the threshold. Combing the threshold of amplitude and time to detect the clench action pattern.

3 Experiment and Results

3.1 Subject and Experiment

Ten healthy volunteers (five males and five females, mean age 22.8 ± 2.3 years) were recruited to participate in system verification experiment, all subjects had normal or corrected to normal vision. EEG and EMG signals were simultaneously collected using the Neuroscan signal acquisition system with a sampling rate of 1000 Hz. Each participant was instructed to complete the control task following the indicated icon in accordance with the prescribed procedures. There were 37 times of target selection and confirmation commands, five return and two switch commands in the experiment.

3.2 Evaluation

The correct control output was recorded only once the target selection and the target confirmation were both correct. The Selection Accuracy is the ratio of the command number to the total times of target selection operation. The Confirmation Accuracy is the ratio of the confirmation times to the total number of correct selection times. The Control Accuracy is the ratio of the correct command output number to the number of target commands. The Return Accuracy is the ratio of the correct return number to the total number of return operation times. The Switch Accuracy is the ratio of the correct switch number to the total number of switch operation times.

3.3 Results

Table 1. Accuracy of Commands

	Selection Accuracy	Confirmation Accuracy	Control Accuracy	Return Accuracy	Switch Accuracy
N1	100.0%	100.0%	100.0%	100.0%	100.0%
N2	92.5%	100.0%	100.0%	83.3%	100.0%
N3	97.4%	100.0%	100.0%	100.0%	100.0%
N4	100.0%	100.0%	100.0%	100.0%	66.7%
N5	97.4%	97.4%	100.0%	83.3%	100.0%
N6	100.0%	100.0%	100.0%	100.0%	100.0%
N7	100.0%	100.0%	100.0%	100.0%	66.7%
N8	88.1%	97.4%	100.0%	100.0%	100.0%
N9	94.9%	97.4%	100.0%	71.4%	66.7%
N10	92.5%	100.0%	100.0%	83.3%	100.0%
Average	96.3%	99.2%	100.0%	92.0%	90.0%

As shown in Table 1, the averaged selection accuracy for ten subjects was 96.3%, and there were four subjects who obtained correct target selection and confirmation completely. The averaged confirmation accuracy of all subjects was 99.2%, and there were seven subjects whose target-confirmation accuracy rate was 100%,. There were five subjects who had incorrect target-selection, but there was no confirmation after all the wrong selection, so the control accuracy of the system was 100%. Four subjects failed to correctly control all the return commands, the accuracy of two-time clenching twice for return command averaged as 92%. Three subjects failed to correctly control all the switch commands, the accuracy of long-time clench for switch command averaged as 90.0%.

4 Discussion

The interface of the system is simple, the graphic logo and visual feedback improves interactivity of the system without interfering the stimulus. From the experiment of healthy young subjects who were first time use BCI system, the average recognition of SSVEP reached a high accuracy. After selecting the target, users can judge whether it is the current operation intention through the presented recognition result. Therefore no one made wrong confirmation, which effectively avoids the wrong output and ensure safety of the device control.

In the system, one channel EMG signal and four channels of EEG signals are used to build an hBCI which can implement complex control in home environment with less input signal. The EMG patterns recognition of temporal muscle also achieved high accuracy, effectively using a simple clench motion achieved the confirmation of selected target. The introduction of EMG pattern enriched the function of the system, realized the switch between different interfaces. And the system is Plug&Play which can be closed at any time and woke up at idle state, thereby also reducing the possibility of wrong operation.

The function of this home environment control system is easy to expand, which can be used in different environment, by adjusting function according to the actual need. The hBCI system can achieve hand-free home environment control, its high flexibility and security in control also provides the reliability for the application to paralyzed patients.

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Conflict of Interest

The authors declare that they have no conflict of interest.

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Quantitative EEG in Mild Cognitive Impairment by AR Spectral and Multi-scale Entropy Analysis

Xiaoke Chai, Zhimin Zhang, Guiming Cao, Yangting lu, Guitong Liu, Haijun Niu*

Abstract—**To study the performance of linear and nonlinear methods in distinguishing mild cognitive impairment (MCI) subjects from healthy elderly people by the abnormality of electroencephalograph (EEG), characteristics obtained from autoregressive (AR) spectral and multi-scale entropy (MSE) analysis were applied. EEG Signals were computed to obtain Alpha/Theta and long scale entropy. The results indicated that combining the two features showed better classification ability.**

I. INTRODUCTION

MCI represents the early stage of neurodegenerative disorder in elderly, including AD. Effective diagnosis for MCI is very important, besides subjective neuropsychological test, quantitative EEG recordings in rest state provide a promising methodology for the rapid detection of MCI [1].

II. METHOD

A. Subject and experiment

After mini-mental state examination (MMSE) and clinical evaluation, 18 volunteers over 60 years old were divided into two groups, including 8 MCI subjects and 10 age-matched normal controls (NC). EEG signal for five minutes in rest state was collected using the Nicolet One EEG acquisition instrument with 16 channels.

B. Signal processing

PSD for each segment of five seconds is estimated by AR model using the burg algorithm. The relative PSD in each frequency band was obtained by normalizing the PSD ratio of each frequency band to the whole band. MSE method is based on sample entropy [2] and the average sample entropy from 13 to 20 scales were calculated as the long scale entropy. The two features, Alpha/Theta and long scale entropy of the two groups in frontal, frontal-central, occipital-parietal and temporal areas of both left and right side were calculated.

III. RESULTS & CONCLUSION

There was significant difference of the alpha/theta value in left frontal area of MCI and NC group. The long scale entropy value of all the areas in MCI was higher than that of NC group, as shown in figure 1.

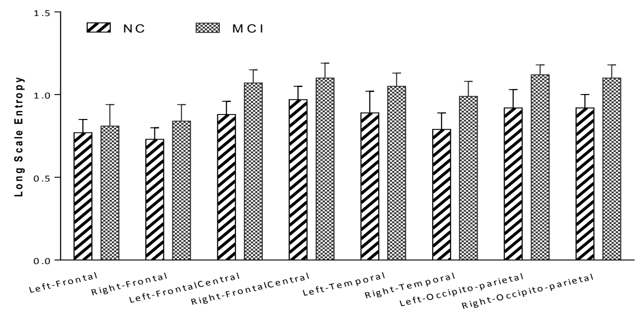

Figure 1. Long scale entropy in different brain areas

The area under Receiver operating characteristic curve (AUC) was introduced to compare the ability of features to distinguish MCI from NC group. The AUC of Alpha/Theta, long scale entropy and the combined feature calculated from them was shown in TABLE I. The AUC of combined feature in all areas of left side was more than 0.7, and can discriminate MCI from NC group, with AUC reaching 0.79.

TABLE I. AUC OF THREE FEATURES

	Alpha/ Theta	Long Scale Entropy	Combined Feature
L-Frontal	**0.76***	**0.55**	**0.79***
L-Frontal Central	**0.48**	**0.73***	**0.70***
L-Temporal	**0.69**	**0.58**	**0.75***
L-Occipito Parietal	**0.55**	**0.69**	**0.76***

*MEANS AUC>0.07

The classification accuracy to distinguish MCI subjects from normal control was greatly improved through combining both linear and nonlinear feature. This indicated that combining PSD and MSE would be a promising method for screening MCI.

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A Hybrid BCI based on SSVEP and EMG of temporalis for Home control

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ABSTRACT

In this study an asynchronous hybrid brain computer interface based on four-channel steady state visual evoked potential (SSVEP) and single-channel electromyogram (EMG) of temporalis was proposed for the control of a virtual home system integrating three devices including a nursing-bed, a television and a telephone. Three clench patterns were introduced to implement SWITCH, RETURN and CONFIRMATION function of the system. Canonical correlation analysis and threshold method were applied to classify EEG and EMG data respectively. In the verification experiments of six participants, there was no occurrence of operation error, which demonstrated that the proposed method of combining EEG and EMG can effectively reduce false operations and enhance the control safety.

Categories and Subject Descriptors

•Human-centered computing →Human computer interaction (HCI) →HCI design and evaluation methods

General Terms

Performance, Design, Reliability.

Keywords

Hybrid brain computer interface; Steady state visual evoked potential (SSVEP); Electromyogram (EMG); Home control.

1. INTRODUCTION

The Brain Computer Interface (BCI) provides a direct communication channel between brain signals and devices without relying on peripheral neuromuscular pathways and can serve as a bridge to control devices for people who are paralyzed due to severe neuromuscular diseases, such as spinal cord injury or amyotrophic lateral sclerosis (ALS) [1]. Paralyzed people need the assistance of a variety of devices including nursing bed and wheelchair. Therefore, a BCI–based home control system integrating multiple devices can help them promote independence and improve quality of life [2].

Electroencephalogram (EEG) signals such as steady-state visual evoked potential (SSVEP), P300 potential and motor-imagery are commonly used to construct BCI systems. Among them, BCI based on SSVEP requires little or no training and has been studied widely. However, most SSVEP-BCIs are synchronous and have high risk of false positives. That means the BCI system may still output control command to device when the user has no control intention, which will cause false operation [3, 4]. Besides that, watching the flashing visual stimuli for a long time can cause visual fatigue and lead to a reduction in recognition accuracy and an increase in operation error [5, 6].

To overcome the shortcomings of single modal BCI, hybrid BCIs have been proposed by combining multiple signals to make use of each one's own advantage and improve the performance of BCI [7, 8]. Erwei Yin et al. developed a hybrid speller based on P300 and SSVEP which achieved higher accuracy and information transmission rate (ITR) compared with the conventional P300 speller [9].Heart rate variability (HRV) obtained from ECG has been introduced into BCI to implement the switch control of BCI [10]. However, HRV may be affected by many factors and lead to false operatives. Muhammad et al. implemented a hybrid BCI based on SSVEP, EOG, EMG and alpha wave. The recognition accuracy of the system could reach to 97%. However the system was complex to use and the delay was severe [11]. Lin et al. implemented a HBCI speller by combining the SSVEP with EMG of hand to increase the number of targets and make a second choice for SSVEP recognition result by discriminating hand motion patterns, which increased both accuracy and information transmission rate of SSVEP-BCI [12]. However, this method is impracticable for people with severe motor dysfunction who have lost control of hands totally. For these people they usually still have control over their facial muscles such as masseter and temporalis. EMG signals of masseter and temporalis can be used for control [13].

In this paper, a hybrid BCI system based on SSVEP and EMG of temporalis for the control of multiple household devices was proposed. EMG signal was introduced into the system to enhance its functionality. An online experiment was conducted to evaluate the performance of the proposed system.

2. METHODS

Subjects

Six healthy subjects (three male and three females; mean age 22.7 ± 2.3 years) volunteered to participate in the experiment. All subjects had normal or corrected normal vision. Before the experiment each subject signed an informed consent.

Data acquisition

EEG and EMG signals were simultaneously collected using the Neuroscan NuAmps signal acquisition system (Neuroscan Inc.) with a sampling rate of 1000 Hz. Four EEG electrodes sites (PO3, PO4, O1, and O2) were selected because SSVEP response in the

结合颞肌肌电的虚拟家居控制系统设计与验证

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摘　要　目的 提出一种脑肌电结合的控制方式，用于对家居系统的控制，以提升控制的安全性和自主性。**方法** 提出了一种结合稳态视觉诱发电位(SSVEP)和颞肌肌电的混合脑机接口控制方式，设计并实现了一个整合 5 种设备的虚拟家居控制系统。其中 SSVEP 用于实现指令选择功能，颞肌肌电用于实现系统开关、界面切换和指令确认功能。脑电和肌电信号分别采用典型相关分析和阈值法处理后，结合系统状态共同决定系统控制指令的生成。6 位受试进行了系统验证实验，定义控制指令比和误操作率等指标评估系统性能。**结果** 6 位受试均成功完成对 5 种家居设备的控制，控制过程中没有发生误操作。设备选择/操控指令的平均指令比为 106.3%。**结论** 本文提出的脑肌电结合的控制方式可以用于家居系统的控制，且能有效减少误操作的发生，提升控制的安全性。

关 键 词 脑机接口；脑电；肌电；稳态视觉诱发电位；家居控制

Design and Verification of Virtual Home Control System with EMG of Temporal Muscle

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Abstract Objective: To propose a method combining electroencephalogram (EEG) and electromyogram (EMG) for the control of home system to enhance the control safety. **Methods:** A hybrid brain-computer interface control method based on Steady-State Visual Evoked Potential (SSVEP) and EMG of temporal muscle was proposed and a virtual home control system integrating five different devices was designed and implemented. SSVEP was used for target selection, and EMG of temporal muscle was used for system switch, graphical user interface switchover and target confirmation. EEG and EMG signals were processed using canonical correlation analysis and threshold method respectively and then determine the generation of system control commands combining EEG and EMG recognition results and system state. Six subjects conducted system verification experiments. Indices including command ratio and false operation rate are defined to evaluate the performance of the system. **Results:** All of the six subjects successfully completed the control for five kinds of devices. No operation error occurred during the control. The average command ratio for Device Selection/Control command was 106.3%. **Conclusions:** The proposed control method of combining EEG and EMG can be used for the control of home system, which can effectively reduce operation errors and enhance the control safety.

Key words: brain-computer interface; electroencephalogram; electromyography; steady-state visual evoked potential; home control

1.引言

脑机接口(Brain Computer Interface ,BCI)是一种可实现神经信号与外部机器直接交互的

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著作权人：北京航空航天大学

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